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STATISTICAL IMPACT ACCELERATION INJURY PREDICTION  
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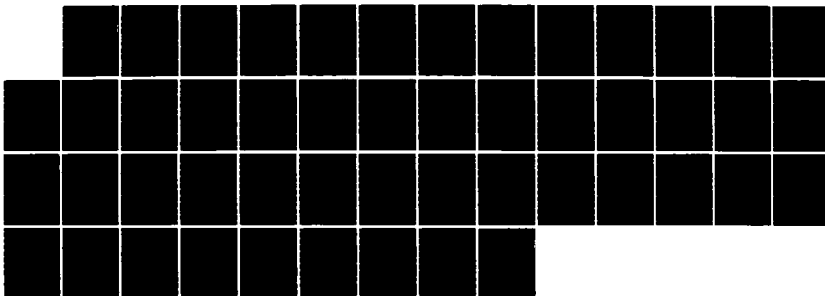
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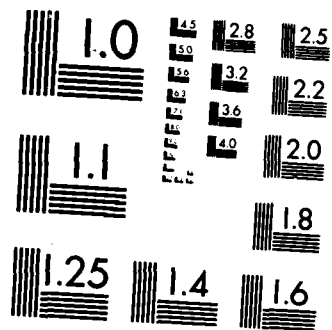
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FINAL REPORT ON STATISTICAL IMPACT  
ACCELERATION INJURY PREDICTION MODELS  
BASED ON  $-G_x$  ACCELERATOR DATA

by

Carl A. Mauro  
Kevin C. Burns  
Dennis E. Smith

— STATISTICS —

— OPERATIONS RESEARCH —

— MATHEMATICS —

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*Applied Research in Statistics - Mathematics - Operations Research*

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## 1. INTRODUCTION

The Naval Biodynamics Laboratory (NBDL) has been engaged in an impact acceleration injury prevention program which has as a major objective the development of a biodynamically faithful anthropomorphic dummy. It is anticipated that this development will provide an essential component to any methodology for evaluating proposed restraint and protection systems. To this end, it is extremely important that preliminary research determines which variables are prime correlates with injury and subsequently establishes tolerance limits, in terms of these variables, for various injury levels.

Since 1974, NBDL has collected an extensive data base from  $-G_x$  accelerator runs on Rhesus and human subjects. Because of safety considerations, experiments with human subjects have been limited to relatively low-level runs. Experiments with Rhesus subjects, however, have been much more extensive, and some have resulted in fatal injury.

As part of its research effort in this area, Desmatics, Inc. has been actively involved in the development of statistically based models to predict injury in Rhesus subjects resulting from indirect head/neck impact acceleration in the  $-X$  direction. Model development focused initially on fatality as the primary injury criteria. Subsequent research, however, has emphasized the development of nonfatal injury prediction models.

Several previous Desmatics technical reports ([2],[7],[8], and [9]) investigated the use of a logistic function in the development of fatality prediction models. Empirical data was used to fit these models and evaluate their ability to accurately predict fatal injuries. The variables considered in those models included the forces and torques in the region of injury, sled

profile and head dynamic response variables, and variables describing the initial position of the head.

The data base analyzed in the aforementioned reports consisted of ninety-three  $-G_x$  accelerator runs on Rhesus subjects, conducted between 1974 and 1980 at NBDL [10]. During 1984 and 1985, seventy-one additional  $-G_x$  accelerator experiments on Rhesus subjects were conducted at NBDL. The objectives of the present technical report are:

- (1) to summarize, update, and consolidate the Desmatics modeling efforts for fatal injury;
- (2) to investigate extending the injury prediction models to include nonfatal injury criteria;
- and (3) to evaluate the accuracy and validity of the prediction models obtained in the modeling efforts.

## 2. METHODS

The logistic model has the following functional form:

$$P(\underline{x}) = \{1 + \exp[-\underline{x}'\underline{\beta}]\}^{-1} \quad (2.1)$$

where  $\underline{x} = (1, x_1, x_2, \dots, x_k)'$  denotes the set of independent (i.e., predictor) variables considered,

$\underline{\beta} = (\beta_0, \beta_1, \dots, \beta_k)'$  denotes the set of parameter values,

and  $P(\underline{x})$  denotes the true probability of injury corresponding to  $\underline{x}$ .

The logistic model sometimes is motivated by threshold theory. For example, suppose that each Rhesus subject has a certain unknown threshold, say  $T$ , such that injury will occur if  $\underline{x}'\underline{\beta} \geq T$  and will not occur if  $\underline{x}'\underline{\beta} < T$ . If the probability distribution of Rhesus thresholds were logistic [which is given in cumulative distribution form in equation (2.1)], model (2.1) would be the appropriate model according to threshold theory. It may be noted that the logistic distribution closely resembles a normal distribution but has proven to be more analytically tractable. Furthermore, the assumption that the threshold of each animal can reasonably be expressed as a linear combination of predictor variables has been discussed in [6].

A stepwise selection procedure ([3] and [4]), in conjunction with model (2.1), was used to determine the inclusion of predictor variables in model construction. The stepwise selection method begins with no variables in the model, except for a constant term, and inserts variables in turn until no further improvement can be made. The order of insertion is determined by using a likelihood-ratio test [5] as a measure of the importance of variables not yet in the model equation. In addition, the stepwise procedure can also



remove a variable that was entered at an earlier stage in the procedure. Accordingly, judgements on the insertion or removal of variables are made at every stage in the stepwise selection procedure.

The models presented and analyzed in this report were based on two sets of injury data. The first of these, which will henceforth be referred to as Data Set A, consisted of ninety-three  $-G_x$  accelerator runs on Rhesus subjects, conducted between 1974 and 1980 at NBDL. The other data set, which will henceforth be referred to as Data Set B, consisted of seventy-one  $-G_x$  accelerator runs on Rhesus subjects, conducted during 1984 and 1985 at NBDL. Data Sets A and B are listed in Appendices A and B, respectively. Table 1 provides a brief description of the variables, including their associated codes and units of measurement, comprising the two data sets.

In Data Set A, four sled profile variables (PSA, ESV, ROO, and DOP), two head initial condition variables (PHB and PHC), and nine head dynamic response variables (QHA, QHB, QHC, RHA, RHB, RHC, AAX, AAY, and AAZ) were available for analysis. In Data Set B, these fifteen variables and an additional head initial condition variable (PHA) were available for analysis. Furthermore, because of symmetry considerations, absolute values of several of the variables were used in model development. These were RHA, RHC, QHA, QHC, AAY, PHA, and PHC.

In Data Set A, two sled runs, Run Nos. LX1363 and LX1365, were omitted from any model development. Run No. LX1363, which was a fatal experiment, was omitted due to suspicion that subject animal A03935 was compromised in a previous high-level run (Run No. LX1362) made earlier that day. Run No. LX1365, which also was a fatal experiment, was omitted due to suspect data quality. Of the remaining ninety-one sled experiments in Data Set A, eleven

<u>VARIABLE</u>	<u>DESCRIPTION</u>
RUN	RUN ID NUMBER
SUBJECT	ANIMAL ID NUMBER
FATALITY	FATAL (1) OR NONFATAL (0)
INJURY <sup>+</sup>	GRADED INJURY (0=No injury, 1=Least severe, ..., 4=Fatal)
PSA	PEAK SLED ACCELERATION (m/sec <sup>2</sup> )
ESV	END STROKE VELOCITY (m/sec)
ROO	RATE OF SLED ACCELERATION ONSET (m/sec <sup>3</sup> )
DOP	DURATION OF PEAK SLED ACCELERATION (msec)
QHA*	PEAK HEAD ANGULAR ACCELERATION, X COMPONENT (rad/sec <sup>2</sup> )
QHB	PEAK HEAD ANGULAR ACCELERATION, Y COMPONENT (rad/sec <sup>2</sup> )
QHC*	PEAK HEAD ANGULAR ACCELERATION, Z COMPONENT (rad/sec <sup>2</sup> )
RHA*	PEAK HEAD ANGULAR VELOCITY, X COMPONENT (rad/sec)
RHB	PEAK HEAD ANGULAR VELOCITY, Y COMPONENT (rad/sec)
RHC*	PEAK HEAD ANGULAR VELOCITY, Z COMPONENT (rad/sec)
AAX	PEAK HEAD LINEAR ACCELERATION, X COMPONENT (m/sec <sup>2</sup> )
AAY*	PEAK HEAD LINEAR ACCELERATION, Y COMPONENT (m/sec <sup>2</sup> )
AAZ	PEAK HEAD LINEAR ACCELERATION, Z COMPONENT (m/sec <sup>2</sup> )
PHA* <sup>+</sup>	INITIAL ROLL ANGLE OF THE HEAD (rad)
PHB	INITIAL PITCH ANGLE OF THE HEAD (rad)
PHC*	INITIAL YAW ANGLE OF THE HEAD (rad)

---

\*absolute value of variable was used in model development

<sup>+</sup>variable was not available in Data Set A

Table 1. Description of Variables.

resulted in fatal injury.

In Data Set B, only one sled run, Run No. LX4824, was omitted from any model development. This sled experiment, which was nonfatal, was deleted due to suspect data quality resulting from sled breakup upon impact. Of the remaining seventy sled experiments in Data Set B, only two resulted in fatality.

### 3. FATALITY MODELS

This section summarizes and discusses the Desmatics modeling efforts regarding the development of fatality prediction models. The initial phase of these efforts focused on developing and comparing fatality prediction models using the "historical" data base (i.e., Data Set A). The resulting models were subsequently used to obtain predicted probabilities of fatality for the more recent series of sled experiments (i.e., Data Set B).

Because Data Set B had only two fatal sled experiments, there was insufficient information to attempt to develop fatality models based solely on this data set. Consequently, the final phase of the modeling efforts focused on developing fatality models using all available data (i.e., Data Sets A and B combined).

#### 3.1 Phase I: Models Based on Data Set A

Data Set A contained ninety-one sled experiments and fifteen predictor variables for analysis. Four predictive models were obtained using this data set. The first of these was developed from the set of four sled profile variables, the second from the set of four sled profile and two head initial condition variables, the third from the set of nine head dynamic response variables, and the fourth from the combined set of fifteen variables.

It should be pointed out that different sets of sled experiments were used to develop each of these four models. This was necessary because not every predictor variable was measured in each sled experiment. For example, there were a number of sled experiments in Data Set A in which no data was

available on any of the head dynamic response variables. In fact, out of the ninety-one sled experiments, there were only thirteen in which the complete set of fifteen predictor variables was measured. In general, therefore, the particular set of sled experiments used to develop a prediction model depended on the variables considered for inclusion in that model.

It should also be noted that some of the Rhesus subjects were run more than once. Consequently, some dependencies most likely exist in the data as a result of having multiple sled runs with the same animal. However, the assumption is made here that any resulting bias in the parameter estimates is small. If there is a bias, it should result in a model that tends to overpredict probabilities.

#### 3.1.1 Sled Profile Variables

Four sled profile variables were considered in model development: PSA, ESV, ROO, and DOP. It was found that the complete set of these sled variables was available on eighty sled runs in Data Set A. Of these eighty runs, ten were fatal.

The "best" one-variable model, as determined by the stepwise selection procedure, was based on PSA, peak sled acceleration. There was no two-variable model involving the four sled profile variables which offered any significant improvement over the PSA-based model.

As already noted, there were eighty sled experiments in Data Set A in which all four of the sled profile variables were measured. PSA alone, however, was available for every sled experiment in Data Set A. Consequently, in order to utilize the maximum amount of information available, the PSA-based

model was subsequently fit to the complete set of sled experiments in Data Set A. That model was given by

$$\hat{P}_F = \{1 + \exp[13.777 - .012169(\text{PSA})]\}^{-1} \quad (3.1)$$

where  $\hat{P}_F$  denotes the predicted probability of fatal injury.

This, in fact, illustrates the basic approach followed in obtaining the models presented in this report. First, a set of predictor variables is considered for inclusion in a model. Then, the stepwise selection procedure is used to determine which variables are actually to be included in the final model. The selected variables are then fit to the maximum set of sled experiments to obtain the estimated model parameters.

#### 3.1.2 Sled Profile and Head Initial Condition Variables

In addition to the four sled profile variables, two head initial condition variables, PHB and  $|\text{PHC}|$ , were also considered in model development. There were seventeen sled runs, which included ten fatal experiments, available for analysis on these six predictor variables. PHA, another head initial condition variable, was unavailable in Data Set A, and therefore was not included in this analysis.

As determined by the stepwise selection procedure, the best one-variable model was based on PSA. This model could be improved on, however, by the addition of  $|\text{PHC}|$ , the absolute initial yaw angle of the head. Any further additions to this model did little to enhance predictive ability.

The two-variable model based on PSA and  $|\text{PHC}|$  was given by

$$\hat{P}_F = \{1 + \exp[17.679 - .014587(PSA) - 2.5612|PHC|]\}^{-1} \quad (3.2)$$

where  $\hat{P}_F$  denotes the predicted probability of fatal injury. The coefficients in model (3.2) were obtained by fitting the PSA and |PHC| variables to nineteen sled runs, including eleven fatalities, which had data available on those two variables.

### 3.1.3 Head Dynamic Response Variables

Nine head dynamic response variables were considered in model development: |QHA|, QHB, |QHC|, |RHA|, RHB, |RHC|, AAX, |AAY|, and AAZ. A total of sixty-three sled runs, which included seven fatalities, were available for analysis on these nine variables.

The best one-variable model, as determined by the stepwise selection procedure, was based on AAZ, the peak Z-component of head linear acceleration. No further additions resulted in any significant improvement to this model.

In addition to the aforementioned sixty-three runs, one additional run (nonfatal) had data available for the AAZ variable. These sixty-four runs were subsequently used to obtain the following AAZ-based model:

$$\hat{P}_F = \{1 + \exp[7.03 + .0053089(AAZ)]\}^{-1} \quad (3.3)$$

where  $\hat{P}_F$  denotes the predicted probability of fatal injury.

### 3.1.4 Combined Sled, Head Initial Condition, and Dynamic Response Variables

The combined set of fifteen predictor variables was considered for model

development. There were thirteen sled runs, which included seven fatalities, available for analysis on the combined set of variables.

The best one-variable model, as determined by the stepwise selection procedure, was based on AAZ. A significantly improved model was subsequently achieved by the addition of |PHC| to the model. Because only thirteen sled experiments were used in the analysis, enlarging the model to include more than two variables would most likely result in an overfit model. Such models generally fit the data very well but are extremely dangerous for prediction.

Other than the indicated thirteen sled experiments, no additional runs had data available on both AAZ and PHC. The resulting model based on AAZ and |PHC| was given by

$$\hat{P}_F = \{1 + \exp[9.1391 + .0056925(AAZ) - 4.268|PHC|]\}^{-1} \quad (3.4)$$

where  $\hat{P}_F$  denotes the predicted probability of fatal injury.

### 3.1.5 Comparison of Models

The four fatality prediction models presented in sections 3.1.1 through 3.1.4 were based on the following sets of predictor variables:

<u>Model</u>	<u>Variable(s)</u>
3.1	PSA
3.2	PSA and  PHC
3.3	AAZ
3.4	AAZ and  PHC

where PSA denotes the peak sled acceleration, PHC denotes the initial yaw angle of the head, and AAZ denotes the peak Z-component of head linear



acceleration. Unfortunately, because these models were developed from different sets of sled experiments, they cannot be compared directly with each other. For example, the head dynamic response model, (3.3), was based on a set of sixty-four sled experiments. However, many of these experiments were relatively low-level (<40G) runs, which are inherently much easier to predict than are high-level runs. In contrast, the thirteen sled experiments used to develop the combined-variables model, (3.4), were all high-level (>85G) runs.

It was noted, however, that the set of thirteen sled experiments used to develop model (3.4) was common to each of the other three sets of sled experiments used in model development. Thus, some assessment of the relative performance of the various sets of predictor variables may be obtained by comparing the predicted probabilities of fatal injury for these thirteen sled experiments. Of course, in order to ensure a common basis of comparison, the variables in models (3.1), (3.2), and (3.3) were refitted specifically to this set of data.

Performance was measured using the Brier statistic [1] which is defined as

$$B = \frac{1}{n} \sum_{i=1}^n (O_i - \hat{P}_i)^2$$

where  $O_i$  is the observed probability of fatality (0 or 1) for the  $i^{\text{th}}$  observation,  $\hat{P}_i$  is the corresponding predicted probability of fatality, and  $n$  is the number of observations. The Brier statistic expresses the average quadratic loss; thus, a smaller value of  $B$  indicates better performance. In addition, the square root of the Brier statistic is a measure of the average misprediction.

The Brier statistics calculated for each variable set were as follows:

<u>Set</u>	<u>Variable(s)</u>	<u>B</u>	<u><math>\sqrt{B}</math></u>
#1	PSA	.212	.460
#2	PSA and  PHC	.134	.366
#3	AAZ	.201	.448
#4	AAZ and  PHC	.148	.385

Not surprisingly, a comparison of these statistics indicates that the two two-variable sets, #2 and #4, were better than either of the two one-variable sets, #1 and #3. Furthermore, variable sets #2 and #4 were fairly comparable with each other, as were sets #1 and #3.

To provide a "baseline" for comparison, perhaps the simplest prediction model is that which predicts a common probability of fatality, as given by the observed proportion of fatalities in the data. Of the thirteen sled experiments, 53.8% (i.e., 7/13) resulted in fatal injury. The prediction model whereby  $\hat{P}_F = 53.8\%$  for each sled experiment has an associated Brier statistic of  $B = .249$ . As indicated above, variable set #2 had the smallest Brier statistic given by  $B = .134$ . This represents about a 46% reduction of the baseline value. The reduction in the baseline value can, in some sense, be regarded as the percentage of the total variation in the data that can be explained by the predictor variables. Note that the Brier statistics of sets #1 and #3, which are the two one-variable sets, represent only a 15% and a 19% reduction, respectively, in the baseline value. The use of variable set #4 resulted in a 41% reduction in the baseline value.

Regardless of which variable set is used, a large percentage of the total variation in the data remains unexplained. However, it should be noted that each of the thirteen sled experiments under consideration was close to the

threshold level for fatality. These runs are inherently difficult to predict, especially if there are wide differences in susceptibility between subjects. Since there is no data available for estimating differences in susceptibility, it is impossible to determine at this time whether the failure to more fully explain the data is caused by inadequacy of the models or by intrinsic variability resulting from differences between subjects.

If there are wide differences in susceptibility between subjects, those differences must be taken into account in order to construct a good prediction model. Since there is no way to measure susceptibility directly, it must be incorporated into the model indirectly through the use of related variables (e.g., anthropometric variables). Further research is needed in order to identify such variables.

### 3.2 Predicted Fatality for Data Set B

The four fatality prediction models (3.1), (3.2), (3.3), and (3.4) were used to rank the sled experiments in Data Set B in order of predicted severity. These rankings are provided in Tables 2a, 2b, 2c, and 2d. Included in these tables are the lower and upper 95% confidence limits associated with each predicted probability of fatality. Also included is the level of graded injury in each sled experiment, where 0=No Injury, 1=Least Severe, ..., 4=Fatal. Graded injury data was not generally available for the sled experiments in Data Set A.

There were only two fatalities in Data Set B. These were Run Nos. LX4801 and LX4803. As can be seen from Tables 2a, 2b, 2c, and 2d, all four models failed to predict that LX4803 would result in fatality. On the other hand,

<u>Run</u>	<u>Graded Injury</u>	<u>PSA</u>	<u>Lower 95% Confidence Limit</u>	<u>Predicted Probability of Fatality</u>	<u>Upper 95% Confidence Limit</u>
LX4787	0	90.1	.00	.00	.01
LX4792	0	95.5	.00	.00	.01
LX4819	0	100.5	.00	.00	.01
LX4809	0	100.6	.00	.00	.01
LX4813	0	100.7	.00	.00	.01
LX4800	0	100.9	.00	.00	.01
LX4821	0	100.9	.00	.00	.01
LX4815	0	101.0	.00	.00	.01
LX4807	0	101.1	.00	.00	.01
LX4823	0	101.1	.00	.00	.01
LX4811	0	101.2	.00	.00	.01
LX4802	0	101.6	.00	.00	.01
LX4817	0	101.8	.00	.00	.01
LX4804	0	102.0	.00	.00	.01
LX4798	0	104.3	.00	.00	.01
LX4782	0	124.2	.00	.00	.01
LX4781	0	124.5	.00	.00	.01
LX5122	0	197.1	.00	.00	.02
LX5159	0	199.4	.00	.00	.02
LX5127	0	200.1	.00	.00	.02
LX5137	0	200.5	.00	.00	.02
LX5134	0	201.6	.00	.00	.02
LX5140	0	202.7	.00	.00	.02
LX5149	0	202.9	.00	.00	.02
LX5143	0	203.4	.00	.00	.02
LX5146	0	203.6	.00	.00	.02
LX5154	0	204.6	.00	.00	.02
LX5123	0	403.7	.00	.00	.05
LX5128	0	406.4	.00	.00	.05
LX5132	0	408.2	.00	.00	.05
LX5135	0	409.2	.00	.00	.05
LX5151	0	410.8	.00	.00	.05
LX5150	0	411.0	.00	.00	.05
LX5157	0	411.1	.00	.00	.05
LX5155	0	412.0	.00	.00	.05
LX5152	2	413.5	.00	.00	.05
LX5138	0	413.9	.00	.00	.05
LX5156	0	415.2	.00	.00	.05
LX4808	0	544.4	.00	.00	.11
LX4820	0	545.0	.00	.00	.11
LX4810	0	545.2	.00	.00	.11
LX4788	0	552.2	.00	.00	.11
LX4783	0	556.0	.00	.00	.11
LX4784	0	625.1	.00	.00	.17
LX4814	0	692.5	.00	.00	.25
LX4789	0	699.0	.00	.01	.26
LX4818	0	700.0	.00	.01	.26
LX4816	0	700.3	.00	.01	.26
LX5125	0	720.0	.00	.01	.30
LX5160	0	723.9	.00	.01	.30
LX5129	0	724.5	.00	.01	.30
LX5131	0	724.5	.00	.01	.30
LX5147	3	727.7	.00	.01	.31
LX5141	0	730.6	.00	.01	.31
LX5144	3	731.6	.00	.01	.32
LX5164	0	732.5	.00	.01	.32
LX5161	0	733.0	.00	.01	.32
LX5162	0	734.4	.00	.01	.32
LX5165	0	744.3	.00	.01	.34
LX4785	0	777.1	.00	.01	.41
LX4790	0	834.4	.00	.03	.55
LX4806	0	838.5	.00	.03	.56
LX4822	0	842.6	.00	.03	.57
LX4812	1	845.4	.00	.03	.58
LX4803	4	884.1	.00	.05	.67
LX4786	0	940.0	.00	.09	.80
LX4795	0	985.1	.00	.14	.88
LX4791	0	988.4	.00	.15	.88
LX4801	4	994.7	.00	.16	.89
LX4799	1	1039.6	.01	.24	.94

Table 2a. Fatality Probabilities in Order of Predicted Severity Based on Model (3.1)

Run	Graded Injury	PSA	PHC	Lower 95% Confidence Limit	Predicted Probability of Fatality	Upper 95% Confidence Limit
LX4815	0	101.0	.	.	.	.
LX4816	0	700.3	.	.	.	.
LX4813	0	100.7	.01	.00	.00	.68
LX4821	0	100.9	.10	.00	.00	.68
LX4823	0	101.1	.10	.00	.00	.68
LX4807	0	101.1	.11	.00	.00	.68
LX4800	0	100.9	.17	.00	.00	.67
LX4787	0	90.1	.38	.00	.00	.66
LX4782	0	124.2	.22	.00	.00	.67
LX4811	0	101.2	.53	.00	.00	.66
LX4804	0	102.0	.59	.00	.00	.66
LX5154	0	204.6	.02	.00	.00	.67
LX5122	0	197.1	.11	.00	.00	.66
LX4802	0	101.6	.67	.00	.00	.65
LX5127	0	200.1	.11	.00	.00	.66
LX5134	0	201.6	.13	.00	.00	.66
LX4781	0	124.5	.60	.00	.00	.65
LX5146	0	203.6	.18	.00	.00	.66
LX4809	0	100.6	.78	.00	.00	.65
LX5140	0	202.7	.22	.00	.00	.65
LX5159	0	199.4	.25	.00	.00	.65
LX5149	0	202.9	.30	.00	.00	.65
LX5143	0	203.4	.30	.00	.00	.65
LX5137	0	200.5	.35	.00	.00	.65
LX4819	0	100.5	.95	.00	.00	.65
LX4817	0	101.8	1.06	.00	.00	.66
LX4798	0	104.3	1.10	.00	.00	.66
LX4792	0	95.5	1.60	.00	.00	.69
LX5135	0	409.2	.02	.00	.00	.63
LX5123	0	403.7	.30	.00	.00	.62
LX5128	0	406.4	.32	.00	.00	.61
LX5157	0	411.1	.30	.00	.00	.62
LX5155	0	412.0	.32	.00	.00	.61
LX5132	0	408.2	.40	.00	.00	.61
LX5156	0	415.2	.38	.00	.00	.61
LX5152	2	413.5	.45	.00	.00	.61
LX5138	0	413.9	.48	.00	.00	.61
LX5151	0	410.8	.50	.00	.00	.61
LX5150	0	411.0	.52	.00	.00	.61
LX4783	0	556.0	.00	.00	.00	.62
LX4820	0	545.0	.21	.00	.00	.60
LX4788	0	552.2	.30	.00	.00	.59
LX4808	0	544.4	.45	.00	.00	.59
LX4810	0	545.2	.75	.00	.00	.58
LX4784	0	625.1	.30	.00	.00	.58
LX4814	0	692.5	.18	.00	.00	.58
LX5144	3	731.6	.00	.00	.00	.60
LX5164	0	732.5	.00	.00	.00	.60
LX5125	0	720.0	.08	.00	.00	.59
LX5160	0	723.9	.07	.00	.00	.59
LX5165	0	744.3	.00	.00	.00	.59
LX5162	0	734.4	.06	.00	.00	.59
LX5161	0	733.0	.07	.00	.00	.59
LX5129	0	724.5	.14	.00	.00	.58
LX5141	0	730.6	.15	.00	.00	.58
LX5131	0	724.5	.20	.00	.00	.58
LX5147	3	727.7	.30	.00	.00	.57
LX4785	0	777.1	.08	.00	.00	.58
LX4818	0	700.0	.65	.00	.00	.56
LX4789	0	699.0	.80	.00	.00	.57
LX4806	0	838.5	.15	.00	.01	.57
LX4822	0	842.6	.15	.00	.01	.57
LX4803	4	884.1	.10	.00	.01	.58
LX4790	0	834.4	.45	.00	.01	.55
LX4812	1	845.4	.40	.00	.01	.55
LX4786	0	940.0	.00	.00	.02	.59
LX4801	4	994.7	.00	.00	.04	.60
LX4791	0	988.4	.25	.00	.07	.57
LX4795	0	985.1	.90	.06	.27	.68
LX4799	1	1039.6	.80	.13	.39	.73

Table 2b. Fatality Probabilities in Order of Predicted Severity  
Based on Model (3.2)

<u>Run</u>	<u>Graded Injury</u>	<u>AAZ</u>	<u>Lower 95% Confidence Limit</u>	<u>Predicted Probability of Fatality</u>	<u>Upper 95% Confidence Limit</u>
LX4815	0	.	.	.	.
LX4816	0	.	.	.	.
LX4786	0	.	.	.	.
LX4806	0	900.	.00	.00	.01
LX4795	0	700.	.00	.00	.01
LX4789	0	470.	.00	.00	.02
LX4788	0	400.	.00	.00	.02
LX4810	0	240.	.00	.00	.03
LX4808	0	200.	.00	.00	.04
LX4782	0	65.	.00	.00	.05
LX4807	0	30.	.00	.00	.05
LX4800	0	30.	.00	.00	.05
LX4792	0	28.	.00	.00	.05
LX4819	0	24.	.00	.00	.05
LX4811	0	21.	.00	.00	.05
LX4813	0	-18.	.00	.00	.05
LX4809	0	-27.	.00	.00	.05
LX4821	0	-32.	.00	.00	.05
LX4802	0	-35.	.00	.00	.05
LX5127	0	-42.	.00	.00	.06
LX4781	0	-43.	.00	.00	.06
LX4817	0	-43.	.00	.00	.06
LX4787	0	-52.	.00	.00	.06
LX4804	0	-57.	.00	.00	.06
LX4798	0	-60.	.00	.00	.06
LX4823	0	-70.	.00	.00	.06
LX5122	0	-70.	.00	.00	.06
LX5154	0	-82.	.00	.00	.06
LX5134	0	-82.	.00	.00	.06
LX5146	0	-85.	.00	.00	.06
LX5137	0	-92.	.00	.00	.06
LX5159	0	-100.	.00	.00	.06
LX5140	0	-125.	.00	.00	.06
LX5149	0	-140.	.00	.00	.07
LX5143	0	-180.	.00	.00	.07
LX5138	0	-190.	.00	.00	.07
LX5150	0	-205.	.00	.00	.08
LX5135	0	-215.	.00	.00	.08
LX5131	0	-220.	.00	.00	.08
LX5152	2	-240.	.00	.00	.08
LX5151	0	-240.	.00	.00	.08
LX5128	0	-280.	.00	.00	.09
LX5155	0	-280.	.00	.00	.09
LX5157	0	-310.	.00	.00	.09
LX5156	0	-320.	.00	.00	.09
LX4783	0	-350.	.00	.01	.10
LX5123	0	-370.	.00	.01	.10
LX5132	0	-400.	.00	.01	.11
LX4822	0	-400.	.00	.01	.11
LX5129	0	-410.	.00	.01	.11
LX4820	0	-430.	.00	.01	.12
LX4814	0	-450.	.00	.01	.12
LX4818	0	-450.	.00	.01	.12
LX5164	0	-500.	.00	.01	.13
LX5160	0	-500.	.00	.01	.13
LX5141	0	-500.	.00	.01	.13
LX4790	0	-500.	.00	.01	.13
LX5162	0	-510.	.00	.01	.13
LX4799	1	-510.	.00	.01	.13
LX5161	0	-520.	.00	.01	.14
LX5125	0	-550.	.00	.02	.15
LX4803	4	-550.	.00	.02	.15
LX4791	0	-600.	.00	.02	.16
LX4812	1	-610.	.00	.02	.16
LX4784	0	-680.	.00	.03	.19
LX5144	3	-710.	.01	.04	.20
LX5147	3	-850.	.02	.07	.27
LX4785	0	-1100.	.09	.23	.50
LX5165	0	-1200.	.14	.34	.63
LX4801	4	-2250.	.70	.99	1.00

Table 2c. Fatality Probabilities in Order of Predicted Severity Based on Model (3.3)

Run	Graded Injury	AAZ	PHC	Lower 95% Confidence Limit	Predicted Probability of Fatality	Upper 95% Confidence Limit
LX4815	0	.	.	.	.	.
LX4816	0	.	.	.	.	.
LX4786	0	.	.	.	.	.
LX4806	0	900.	.15	.00	.00	.94
LX4788	0	400.	.30	.00	.00	.89
LX4795	0	700.	.90	.00	.00	.94
LX4813	0	-18.	.01	.00	.00	.84
LX4807	0	30.	.11	.00	.00	.84
LX5154	0	-82.	.02	.00	.00	.83
LX4800	0	30.	.17	.00	.00	.84
LX4782	0	65.	.22	.00	.00	.85
LX4821	0	-32.	.10	.00	.00	.83
LX5127	0	-42.	.11	.00	.00	.83
LX4789	0	470.	.80	.00	.00	.91
LX4808	0	200.	.45	.00	.00	.87
LX4823	0	-70.	.10	.00	.00	.83
LX5122	0	-70.	.11	.00	.00	.83
LX5134	0	-82.	.13	.00	.00	.82
LX5146	0	-85.	.18	.00	.00	.82
LX5135	0	-215.	.02	.00	.00	.80
LX5159	0	-100.	.25	.00	.00	.82
LX5140	0	-125.	.22	.00	.00	.81
LX4810	0	240.	.75	.00	.00	.89
LX4787	0	-52.	.38	.00	.00	.83
LX4783	0	-350.	.00	.00	.00	.78
LX5137	0	-92.	.35	.00	.00	.82
LX5149	0	-140.	.30	.00	.00	.81
LX5131	0	-220.	.20	.00	.00	.80
LX4811	0	21.	.53	.00	.00	.84
LX5143	0	-180.	.30	.00	.00	.80
LX4781	0	-43.	.60	.00	.00	.84
LX4804	0	-57.	.59	.00	.00	.83
LX5164	0	-500.	.00	.00	.00	.75
LX4822	0	-400.	.15	.00	.00	.76
LX5129	0	-410.	.14	.00	.00	.76
LX5128	0	-280.	.32	.00	.00	.78
LX5155	0	-280.	.32	.00	.00	.78
LX5157	0	-310.	.30	.00	.00	.78
LX4802	0	-35.	.67	.00	.00	.84
LX5138	0	-190.	.48	.00	.00	.80
LX5160	0	-500.	.07	.00	.00	.75
LX5162	0	-510.	.06	.00	.00	.75
LX5161	0	-520.	.07	.00	.00	.74
LX5152	2	-240.	.45	.00	.00	.79
LX4814	0	-450.	.18	.00	.00	.75
LX4820	0	-430.	.21	.00	.00	.75
LX5150	0	-205.	.52	.00	.00	.80
LX5123	0	-370.	.30	.00	.00	.76
LX5156	0	-320.	.38	.00	.00	.78
LX5125	0	-550.	.08	.00	.00	.74
LX4809	0	-27.	.78	.00	.00	.85
LX5141	0	-500.	.15	.00	.00	.74
LX5151	0	-240.	.50	.00	.00	.80
LX4803	4	-550.	.10	.00	.00	.74
LX4819	0	24.	.95	.00	.01	.88
LX5132	0	-400.	.40	.00	.01	.76
LX5144	3	-710.	.00	.00	.01	.72
LX4791	0	-600.	.25	.00	.01	.72
LX4790	0	-500.	.45	.00	.01	.74
LX4817	0	-43.	1.06	.00	.01	.89
LX4798	0	-60.	1.10	.00	.02	.90
LX4784	0	-680.	.30	.00	.02	.70
LX4812	1	-610.	.40	.00	.02	.72
LX4818	0	-450.	.65	.00	.02	.77
LX5147	3	-850.	.30	.00	.05	.67
LX4799	1	-510.	.80	.00	.06	.79
LX4785	0	-1100.	.08	.00	.07	.67
LX4792	0	28.	1.60	.00	.08	.97
LX5165	0	-1200.	.00	.00	.09	.69
LX4801	4	-2250.	.00	.11	.98	1.00

Table 2d. Fatality Probabilities in Order of Predicted Severity  
Based on Model (3,4)

LX4801 was accurately predicted by models (3.3) and (3.4), but was poorly predicted by models (3.1) and (3.2). It may also be noted that all models had fairly wide confidence intervals, as expressed by the difference between the upper and lower confidence limits. Model (3.3), however, provided the narrowest intervals.

The confidence intervals in Tables 2a-2d are wide for two basic reasons. First, dichotomous variables are inherently difficult to predict since so little information is obtained from each experiment. In general, much larger sample sizes are required for these variables than would be required to obtain equivalent precision for continuous variables. The second problem arises from the fact that much of the data used to build these models was obtained from relatively low-level runs and thus contributed little to the model-building process. The runs which are most useful for estimating the parameters of a logistic model are those which are fairly close to the fatality threshold.

The Brier statistics for the four models were as follows:

<u>Model</u>	<u>B</u>	<u><math>\sqrt{B}</math></u>
(3.1)	.025	.157
(3.2)	.031	.177
(3.3)	.017	.131
(3.4)	.015	.123

The baseline Brier value was  $B=.028$ . As indicated from the statistics above, models (3.3) and (3.4) were clearly better than either of (3.1) or (3.2). These latter two models resulted in little or no reduction in the baseline Brier value. Model (3.4) had a Brier value which was slightly less than that for model (3.3). It should be expected, however, that model (3.4) would outperform model (3.3) since (3.4) contains an additional predictor



variable. Furthermore, the Brier statistic of  $B=.015$  associated with model (3.4) represented a 46.4% reduction of the baseline value. This reduction is consistent with that found in section 3.1.5.

It should be noted that the superior performance of the two models which included as a predictor the peak Z-component of head linear acceleration (3.3 and 3.4) can to a large extent be attributed to their predictions for one sled run. That run (LX4801) had a moderately high peak sled acceleration but an extremely high head acceleration. Extreme caution is needed when attempting to draw conclusions from a single experimental run.

With regard to nonfatal injury, it is not unreasonable to expect that a fatality model should predict nonfatal injury to some extent, assuming that the failure mechanism is the same and that injury is more or less a matter of degree. It is difficult to state, however, what magnitude of probability that a fatality model should predict for a specific level of nonfatal injury.

As can be seen from Tables 2a, 2b, 2c, and 2d, sled experiments with nonzero graded injury levels were generally ranked higher in terms of their predicted probability of fatality than were sled experiments involving no injury. The actual ordering of the injuries was not entirely consistent, however, with their severity. For example, fatalities were not always ranked higher than level-3 injuries, which were not always ranked higher than level-2 injuries, and so forth. It was found, though, that model (3.3) provided the most consistent ranking of sled experiments relative to their associated injury severity.

### 3.3 Phase II: Models Based on Data Sets A and B Combined

Desmatics combined Data Sets A and B and consolidated its modeling efforts. As was done previously in Section 3.1, models were developed from the sled profile variables, the sled profile and head initial condition variables, the dynamic response variables, and all variables combined. Although PHA, the initial roll angle of the head, was measured in Data Set B, it was omitted here because it was not available for sled experiments in Data Set A; otherwise, the stepwise selection procedure would have been limited to Data Set B anytime PHA was considered for inclusion in the model.

As before, the stepwise selection method was used to determine the inclusion of predictor variables in the various models. Except for the model developed from the set of sled profile and head initial condition variables, the predictor sets which were selected were the same as those determined previously in Section 3.1. In the case of the sled profile and head initial condition variables, the model based on PSA and  $|PHC|$  was replaced by a model based on PSA and PHB, where PHB is the initial pitch angle of the head. Maximum closure on these models was obtained by refitting the respective variable sets to the complete set of sled experiments in Data Sets A and B which had data available on those variables. The fitted models are summarized in Table 3. For the sake of completeness and comparison, the model based on PSA and  $|PHC|$  is also included in this table.

#### 3.3.1 Comparison of Models

Models (3.5) through (3.9) listed in Table 3 are not directly comparable

<u>Variables</u>	<u>Number of Sled Experiments Used To Fit Model</u>	<u>Number of Fatalities</u>	<u>Fatality Model</u>	
PSA	161	13	$\hat{P}_F = \{1 + \exp[12.403 - .011067(PSA)]\}^{-1}$	(3.5)
PSA and  PHC	87	13	$\hat{P}_F = \{1 + \exp[11.365 - .0098119(PSA) - .88201 PHC \}\}^{-1}$	(3.6)
PSA and PHB	87	13	$\hat{P}_F = \{1 + \exp[12.027 - .011217(PSA) + 2.1569(PHB)]\}^{-1}$	(3.7)
AAZ	131	9	$\hat{P}_F = \{1 + \exp[6.4031 + .0047125(AAZ)]\}^{-1}$	(3.8)
AAZ and  PHC	80	9	$\hat{P}_F = \{1 + \exp[6.9663 + .00497(AAZ) - 2.7425 PHC \}\}^{-1}$	(3.9)

Table 3. Fitted Fatality Models for Combined Data Sets A and B.

because they were not fit to the same set of sled experiments. However, the set of eighty sled experiments used to fit model (3.9) was common to the construction of each of the other four models. Thus, in order to provide a common basis for comparison, models (3.5) through (3.8) were refitted specifically to these eighty runs. The corresponding Brier statistics were as follows:

<u>Variable(s)</u>	<u>B</u>	<u><math>\sqrt{B}</math></u>	<u>Reduction of Baseline</u>
PSA	.054	.232	46%
PSA and  PHC	.052	.228	48%
PSA and PHB	.047	.217	53%
AAZ	.049	.221	51%
AAZ and  PHC	.037	.192	63%

The baseline value of the Brier statistic was  $B=.100$ .

As seen from the statistics above, AAZ was slightly better than PSA as the best single predictor of fatality. In addition, the AAZ-based model was found to have narrower confidence limits than the PSA-based model. The best two-variable model, and best model overall, was that based on AAZ and |PHC|. This model resulted in a 63% reduction of the baseline Brier value.

### 3.3.2 Tolerance Thresholds

An injury tolerance threshold of  $t\%$ , relative to a given prediction model, is defined as the set of values of the predictor variables where injury is predicted for  $t\%$  of the subjects, i.e., where the predicted probability of injury is  $t\%$ . An tolerance threshold of  $t\%$  will be denoted by  $LD_t$ . In the case of a fatality prediction model, the  $LD_t$  represents, of course, a fatality tolerance threshold.

Table 4 shows the  $LD_t$ s corresponding to models (3.5) through (3.9) for

	<u>Model (3.5)</u>	<u>Model (3.6)</u>	<u>Model (3.7)</u>	<u>Model (3.8)</u>	<u>Model (3.9)</u>
LD <sub>5</sub>	x <sub>1</sub> =854.7	x <sub>2</sub> =8.421	x <sub>3</sub> =9.083	x <sub>4</sub> =-734.0	x <sub>5</sub> =4.022
LD <sub>10</sub>	x <sub>1</sub> =922.2	x <sub>2</sub> =9.168	x <sub>3</sub> =9.830	x <sub>4</sub> =-892.5	x <sub>5</sub> =4.769
LD <sub>25</sub>	x <sub>1</sub> =1021.4	x <sub>2</sub> =10.266	x <sub>3</sub> =10.928	x <sub>4</sub> =-1125.5	x <sub>5</sub> =5.867
LD <sub>50</sub>	x <sub>1</sub> =1120.7	x <sub>2</sub> =11.365	x <sub>3</sub> =12.027	x <sub>4</sub> =-1358.7	x <sub>5</sub> =6.966
LD <sub>75</sub>	x <sub>1</sub> =1220.0	x <sub>2</sub> =12.464	x <sub>3</sub> =13.126	x <sub>4</sub> =-1592.0	x <sub>5</sub> =8.065
LD <sub>90</sub>	x <sub>1</sub> =1319.2	x <sub>2</sub> =13.562	x <sub>3</sub> =14.224	x <sub>4</sub> =-1825.0	x <sub>5</sub> =9.163
LD <sub>95</sub>	x <sub>1</sub> =1386.7	x <sub>2</sub> =14.309	x <sub>3</sub> =14.971	x <sub>4</sub> =-1983.5	x <sub>5</sub> =9.910

KEY: x<sub>1</sub>=PSA

x<sub>2</sub>= .0098119(PSA)+.88201 |PHC|

x<sub>3</sub>= .011217(PSA)-2.1569(PHB)

x<sub>4</sub>=AAZ

x<sub>5</sub>= -.00497(AAZ)+2.7425 |PHC|

Table 4. Fatality Tolerance Thresholds

$t=5,10,25,50,75,90$ , and  $95$ . It should be noted that for a single-variable model, the  $LD_t$  can be calculated uniquely. For example, the  $LD_{50}$  (i.e., 50% chance of fatality) for model (3.5) is given by  $PSA=1120.7 \text{ m/sec}^2 = 114.2 \text{ G}$ . For a two-variable model, the  $LD_t$  is represented by the equation of a straight line in the respective variables. For example, the  $LD_{50}$  for model (3.9) is given by any values of  $AAZ$  and  $|PHC|$  which satisfy the equation
 
$$6.9663 = -.00497(AAZ) + 2.7425|PHC|.$$

#### 4. NONFATAL INJURY MODELS

Because graded injury information was not generally available for those sled experiments in Data Set A, the development of nonfatal injury prediction models was necessarily based on an analysis of Data Set B. There was the following injury information in that data set:

<u>Run No.</u>	<u>Graded Injury</u>
LX4799	1
LX4801	4
LX4803	4
LX4812	1
LX5144	3
LX5147	3
LX5152	2
Other	0

where 0=No Injury, 1=Least Severe, ..., 4=Fatal.

The use of the logistic model requires that the response variable has either a value of 0 (i.e., no injury occurs) or 1 (i.e., injury occurs). Accordingly, the following four injury response variables could be defined:

$$I_j = \begin{cases} 0 & \text{if the level of graded injury} < j \\ 1 & \text{if the level of graded injury} \geq j \end{cases}$$

for  $j=1,2,3$ , and 4. Thus, for example,  $I_1=1$  if any (nonzero) level of injury occurs and  $I_1=0$  if no injury occurs. Similarly,  $I_4=0$  if no fatality occurs and  $I_4=1$  if a fatality occurs. Correspondingly, let  $P_j$  denote the probability that  $I_j=1$ . Equivalently,  $P_j$  represents the probability that a graded injury of level  $j$  or greater will occur.

There are two primary issues involving the development of nonfatal injury prediction models which need to be addressed. First, the prime correlates of nonfatal injury need to be determined and compared with those determined

earlier in fatality model development. Secondly, the ability of these models to "separate" or "distinguish" between the various injury levels must be ascertained. For instance, it is reasonable to require that the derived models have the property that  $\hat{P}_1 > \hat{P}_2 > \hat{P}_3 > \hat{P}_4$ . Nonfatal injury prediction models would be of little use if separation of injury levels cannot be achieved.

#### 4.1 Model Development

The development and construction of nonfatal injury prediction models proceeded according to the approach followed in Section 3 when fatality was the dependent variable of interest. Using  $I_1$ ,  $I_2$ , and  $I_3$  as dependent variables, prediction models were developed from the set of sled profile variables, sled profile and head initial condition variables, head dynamic response variables, and all variables combined. The important predictor variables, as determined by the stepwise selection procedure, were essentially the same as those selected previously in the construction of fatality prediction models. This result was encouraging since it suggested that the same, or similar, mechanisms that underlie fatality may also underlie nonfatal injury.

AAZ, the peak Z-component of head linear acceleration, was determined earlier to be the best single predictor of fatality. This variable was similarly found to be the best single predictor of the response variables  $I_1$ ,  $I_2$ , and  $I_3$ . The following AAZ-based nonfatal injury models were obtained:

$$\hat{P}_1 = \{1 + \exp[3.6470 + .0036048(AAZ)]\}^{-1}, \quad (4.1)$$

$$\hat{P}_2 = \{1 + \exp[4.0526 + .0034072(AAZ)]\}^{-1}, \quad (4.2)$$

$$\text{and } \hat{P}_3 = \{1 + \exp[4.9206 + .0042952(AAZ)]\}^{-1}, \quad (4.3)$$



AAZ was measured on sixty-seven of the seventy sled experiments in Data Set B. Models (4.1), (4.2), and (4.3) were fit to these sixty-seven runs, involving seven, five, and four injuries, respectively. For predicting fatality (i.e.,  $I_4$ ), model (3.8), which was developed in Section 3, may be used:

$$\hat{P}_4 = \hat{P}_F = \{1 + \exp[6.4031 + .0047125(AAZ)]\}^{-1}. \quad (3.8)$$

As an indication of whether these models provided separation of the various injury levels, their  $LD_{50}$ s may be compared. The  $LD_{50}$ s of models (4.1), (4.2), (4.3), and (3.8) are -1011.7, -1189.4, -1145.6, and -1358.7 m/sec<sup>2</sup>, respectively. Ideally, the magnitudes of these tolerance thresholds should increase as the injury level increases. As indicated, however, the magnitudes are not strictly increasing. Specifically, the  $|LD_{50}|$  of  $\hat{P}_3$  is less than that of  $\hat{P}_2$ .

Evidently, a graded injury of level-3 severity cannot be separated, in a predictive sense, from an injury of level-2 severity. (This is not surprising since there was only one level-2 injury in the data base.) Therefore, these two levels of injury, at least for this data set, should probably be considered to be of equal severity. This would imply, then, that until further injury information becomes available and can be analyzed, model (4.2) should be used to predict both level-2 and level-3 injuries.

Models (4.1), (4.2), and (3.8) are illustrated graphically in Figure 1. As can be seen from this figure, there is still not complete separation of  $\hat{P}_1$ ,  $\hat{P}_2$ , and  $\hat{P}_F$ , primarily at high negative AAZ levels. For the most part, however, there is adequate separation for prediction. Note that the crossover does not occur until the predicted probability exceeds 90%.

Continuing with its analysis, Desmatics attempted to extend the AAZ-based injury models to two-variable models. Using  $I_1$ ,  $I_2$ , and  $I_3$  as the injury

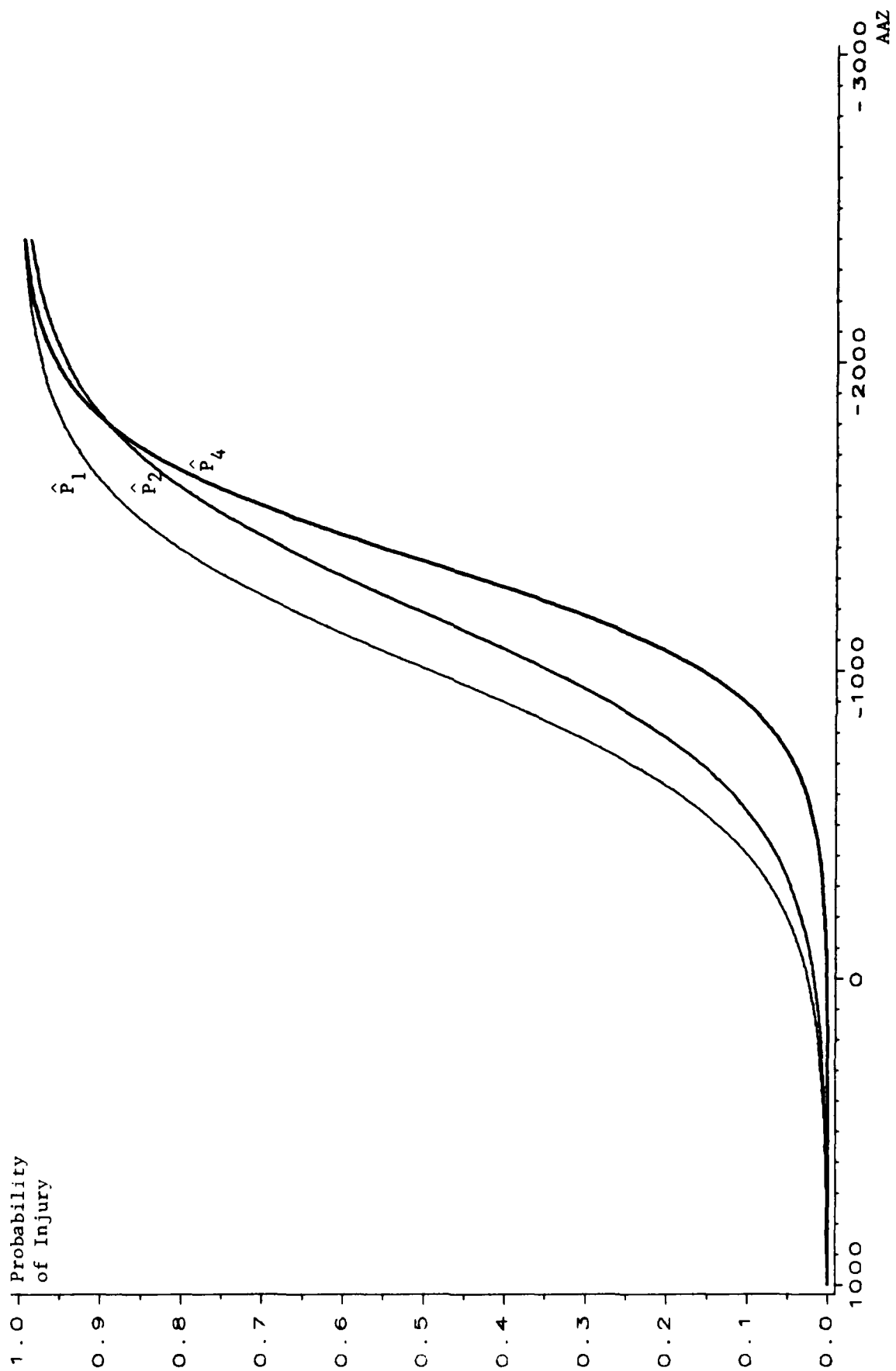


Figure 1. Graphical Illustration of  $\hat{P}_1$ ,  $\hat{P}_2$ , and  $\hat{P}_4$ .

response variables it was found that no two-variable model provided any significant improvement over the predictive abilities of the AAZ-based models. This result was not too surprising owing to the rather limited injury information available in Data Set B.

#### 4.2 Injury Predictions for Data Set A

As previously mentioned, graded injury data was unavailable for Data Set A. However, for completeness, models (4.1), (4.2), and (3.8) were used to obtain nonfatal injury predictions for the ninety-one sled experiments in Data Set A. Table 5 shows the  $\hat{P}_1$ ,  $\hat{P}_2$ , and  $\hat{P}_F$  predictions which were obtained.

Run	Fatality	AAZ	$\hat{P}_1$	$\hat{P}_2$	$\hat{P}_F$
LX454	0	.	.	.	.
LX650	0	.	.	.	.
LX651	0	.	.	.	.
LX653	0	.	.	.	.
LX654	0	.	.	.	.
LX656	0	.	.	.	.
LX657	0	.	.	.	.
LX659	0	.	.	.	.
LX660	0	.	.	.	.
LX661	1	.	.	.	.
LX3006	0	.	.	.	.
LX3007	0	.	.	.	.
LX3008	0	.	.	.	.
LX3009	0	.	.	.	.
LX3010	0	.	.	.	.
LX3011	0	.	.	.	.
LX3012	0	.	.	.	.
LX3013	0	.	.	.	.
LX3014	0	.	.	.	.
LX3015	0	.	.	.	.
LX3016	1	.	.	.	.
LX3017	0	.	.	.	.
LX3018	0	.	.	.	.
LX3019	0	.	.	.	.
LX3020	0	.	.	.	.
LX3031	1	.	.	.	.
LX3033	1	.	.	.	.
LX3027	0	87.	.02	.01	.00
LX3185	0	62.	.02	.01	.00
LX3025	0	42.	.02	.01	.00
LX3708	0	33.	.02	.02	.00
LX3704	0	27.	.02	.02	.00
LX3696	0	12.	.02	.02	.00
LX3703	0	-13.	.03	.02	.00
LX3713	0	-20.	.03	.02	.00
LX3692	0	-26.	.03	.02	.00
LX1081	0	-27.	.03	.02	.00
LX3700	0	-30.	.03	.02	.00
LX3024	0	-45.	.03	.02	.00
LX3695	0	-60.	.03	.02	.00
LX3187	0	-63.	.03	.02	.00
LX3691	0	-67.	.03	.02	.00
LX3189	0	-88.	.03	.02	.00
LX3183	0	-90.	.03	.02	.00
LX3699	0	-102.	.04	.02	.00
LX3707	0	-105.	.04	.02	.00
LX3191	0	-108.	.04	.02	.00
LX3710	0	-117.	.04	.03	.00
LX1899	0	-165.	.05	.03	.00

Table 5. Injury Predictions for Data Set A Sled Experiments.

<u>Run</u>	<u>Fatality</u>	<u>AAZ</u>	$\hat{P}_1$	$\hat{P}_2$	$\hat{P}_F$
LX1898	0	-190.	.05	.03	.00
LX1083	0	-195.	.05	.03	.00
LX1086	0	-235.	.06	.04	.00
LX1890	0	-275.	.07	.04	.01
LX1085	0	-280.	.07	.04	.01
LX1082	0	-290.	.07	.04	.01
LX1084	0	-290.	.07	.04	.01
LX1087	0	-290.	.07	.04	.01
LX1364	0	-300.	.07	.05	.01
LX3697	0	-350.	.08	.05	.01
LX3698	0	-355.	.09	.06	.01
LX3028	0	-365.	.09	.06	.01
LX1889	0	-400.	.10	.06	.01
LX3184	0	-550.	.16	.10	.02
LX1892	0	-560.	.16	.10	.02
LX1900	0	-590.	.18	.11	.03
LX1901	0	-680.	.23	.15	.04
LX3702	0	-680.	.23	.15	.04
LX1891	0	-700.	.25	.16	.04
LX3693	0	-700.	.25	.16	.04
LX3701	0	-720.	.26	.17	.05
LX3715	0	-720.	.26	.17	.05
LX3714	0	-770.	.29	.19	.06
LX3192	1	-775.	.30	.20	.06
LX3694	0	-800.	.32	.21	.07
LX1359	0	-820.	.33	.22	.07
LX3188	0	-850.	.36	.24	.08
LX1362	0	-860.	.37	.25	.09
LX1902	0	-880.	.38	.26	.09
LX3706	0	-910.	.41	.28	.11
LX1903	0	-940.	.44	.30	.12
LX3705	0	-950.	.44	.31	.13
LX3709	1	-1040.	.53	.38	.18
LX3186	0	-1060.	.54	.39	.20
LX3026	1	-1300.	.74	.59	.43
LX3032	0	-1320.	.75	.61	.45
LX1893	0	-1350.	.77	.63	.49
LX1894	0	-1350.	.77	.63	.49
LX1905	1	-1500.	.85	.74	.66
LX1895	1	-1650.	.91	.83	.80
LX1896	1	-1700.	.92	.85	.83
LX1360	1	-2440.	.99	.99	.99

Table 5 (continued). Injury Predictions for Data Set A Sled Experiments.

## 5. SUMMARY AND DISCUSSION

This report documents the construction and evaluation of a set of indirect impact injury prediction models for Rhesus monkeys under  $-G_x$  acceleration. Two data bases were used in model construction: (1) a set of ninety-three accelerator runs conducted between 1974 and 1980 at NBDL (Data Set A) and (2) a set of seventy-one additional runs conducted at NBDL during 1984 and 1985 (Data Set B).

Portions of Data Set A have been analyzed and discussed in previous Desmatics reports. The first step in the current effort was to summarize, consolidate, and update those earlier modeling efforts. Four fatality prediction models were fit to the data, using a stepwise variable selection procedure. The first model was developed from sled profile variables only, the second from sled profile and head initial condition variables, the third from head dynamic response variables, and the fourth from the combined set of all of the variables.

Peak sled acceleration (PSA) was found to be the best predictor of fatality from among the sled profile variables, and the inclusion of additional sled variables did not substantially improve the prediction model. Of the head dynamic response variables, the peak Z-component of head linear acceleration (AAZ) was the best predictor, and again the model could not be substantially improved by the inclusion of additional variables. However, it was found that either of these models could be improved significantly by including a head initial condition variable, the absolute initial yaw angle of the head ( $|PHC|$ ).

Each of the fatality prediction models developed from Data Set A was

refit to the set of thirteen accelerator runs for which all of the relevant predictor variables were available. Performance of the models was evaluated using Brier statistics, which measure the average squared difference between the observations (0 or 1) and the predicted probabilities. The two one-variable models, based on PSA and AAZ, respectively, were found to be fairly comparable, as were the two two-variable models, which included |PHC|.

One measure of model performance is the percentage reduction in the Brier statistic when the model is fit, as compared to a baseline value obtained by predicting a constant average probability of fatality for each accelerator run. This reduction may be thought of as a measure of the amount of variability in the data which can be accounted for by the variables in the model. By this criteria, the one-variable models were able to explain less than 20% of the variability in the data, and the two-variable models only about 50%.

It may not be possible to develop better prediction models using only the predictor variables now available, since prediction accuracy is limited by the inherent variability in the subject population. If there are wide differences in susceptibility between subjects, no model can perform well unless it incorporates some measure of those differences. In any case, some measure of between-subject variability is needed before the current models can be truly evaluated. One way to obtain such an estimate would be to test several subjects under identical conditions and compare the results. It might be possible to relate those results to some measurable anthropometric variables which could then be incorporated into a prediction model.

The four fatality prediction models developed from Data Set A were used to predict fatality for Data Set B. There were only two fatal runs in the

latter set, one of which could not be explained by any of the models. The other fatality was accurately predicted by the two models which included AAZ as a predictor but not by the other two models. Thus, there is some indication that AAZ is a better prediction of fatality than is PSA, but there is not enough evidence for a firm conclusion to be drawn.

Confidence limits were given for the predictions from each of the models and were in all cases fairly wide. In general, large sample sizes are needed to obtain precise predictions for dichotomous variables. It should be noted that the confidence intervals were narrowest for the model based on AAZ alone, although the model based on AAZ and |PHC| gave slightly better predictions. It is not clear which model is preferable, but their predictions are similar enough that it probably makes little difference which is chosen. There is definite evidence that |PHC| is of some value as a predictor variable, but its significance is small compared to that of AAZ.

In order to obtain the best possible fatality prediction models, the two data sets were combined and the modeling process repeated. In three of the four cases, the same predictor variables were selected. The model based on PSA and |PHC|, however, was replaced by a model based on PSA and PHB, where PHB is the initial pitch angle of the head. Once again, AAZ was found to be a slightly better predictor than PSA, and the best model was that based on AAZ and |PHC|.

For Data Set B, injuries were classified at four levels of severity, with the highest level representing fatality. Models were developed for each of these levels based on AAZ, which was found to be the single best predictor of injury. These were too few injuries to allow the development of models with more than one predictor variable.



For each of the graded injury models, the  $LD_{50}$  was calculated. (This is the level of AAZ at which the predicted probability is 50%.) Comparison of the  $LD_{50}$ s showed that the second and third severity levels could not be distinguished in this data set. This result could be spurious, since there were only one level-2 injury and two level-3 injuries, too little data on which to base conclusions. However, for the sake of this analysis, it was necessary to combine the two levels. The remaining three injury prediction models (slight, moderate, fatal) were plotted and shown to be adequately separated except at the highest negative AAZ levels.

The fact that AAZ was found to be the best predictor variable for each level of injury suggests that the same mechanism(s) may be responsible for each type of injury. Furthermore, the  $LD_{50}$ s are estimates of the mean population thresholds for each injury level and may therefore be used as an initial step toward the establishment of a continuous injury scale.

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## APPENDIX A

The following two pages contain a listing of the sled experiments in Data Set A. Periods indicate missing values. A description of the variables is given in Table 1.

RUN	SUBJECT	FATALITY	PSA	ESV	ROO	DOP	QEA	QHB	QHC	RHA	RHB	RHC	AAZ	AAZ	AAZ	PBB	PHC
LX0454	A03146	0	234.6	12.55	31.3												
LX0650	A03146	0	222.0	12.34	34.8												
LX0651	A03146	0	253.6	13.59	31.3												
LX0653	A03146	0	496.2	19.32	27.7												
LX0654	A03146	0	502.2	19.32	27.0												
LX0656	A03146	0	280.8	14.34	30.9												
LX0657	A03146	0	1065.6	27.76	15.5												
LX0659	A03146	0	553.1	20.38	23.6												
LX0660	A03146	0	1052.4	27.72	15.7												
LX0661	A03146	1	1550.6	18.18	8.7												
LX1081	A03921	0	101.2	1.51	1533	49.6	-300	800	1000	-5.8	8.3	12.5	-142	-65	-27	0.69813	0.0000
LX1082	A03921	0	389.4	17.34	872		-860	3750	2100	-11.0	23.0	13.0	-650	-120	-290	0.69813	0.0000
LX1083	A03921	0	375.1	15.36	3512	27.2	-1600	1250	800	-10.0	8.7	5.2	-630	-50	-195		
LX1084	A03921	0	377.2	15.50	3832	27.3	-2200	3750	5700	-18.0	24.0	46.0	-390	-390	-290		
LX1085	A03921	0	374.6	15.35	3478	26.9	-1725	2150	2600	-12.0	15.0	19.0	-630	-145	-280		
LX1086	A03921	0	385.9	15.50	3829	27.3	-2100	1500	2750	-15.0	10.8	24.0	-620	-205	-235		
LX1087	A03921	0	387.4	15.68	3775	26.6	-2700	4500	-4500	-8.0	28.0	-19.0	-720	320	-290		
LX1359	A04099	0	1046.9	31.97	16586	19.2	-11000	14500	14000	-63.0	51.5	60.0	-2630	-900	-820	0.34907	-0.5236
LX1360	A04099	1	1255.7	34.35	21427	17.2	20000	18500	-45000	85.0	45.0	-233.0	-2400	-4200	-2440	0.08727	1.5708
LX1362	A03935	0	1033.5	31.68	17949	21.0	16500	31000	15000	82.0	145.0	110.0	-4000	1700	-860	0.69813	0.5236
LX1363	A03935	1	1204.4	33.51	20762	18.7	-18000	-12000	10000	-60.0	-80.0	36.0	-1800	-400	-840	0.69813	0.0000
LX1364	A03921	0	361.5	16.75	612	26.5	-2200	4300	4000	-27.0	32.5	43.0	-640	-400	-300		
LX1365	A03921	1	1064.2	32.00	13398	18.5	-37000	22600	-57000	-193.0	160.0	-350.0	9200	1500	-1550	-0.34907	1.5708
LX1889	A04101	0	341.0	15.81	1614	27.5	-6500	7500	-6500	-50.0	55.0	-125.0	-1200	1200	-400		
LX1890	A04101	0	325.7	15.40	1561	28.1	-1870	2700	5300	-17.6	12.5	45.0	-535	-285	-275		
LX1891	A03943	0	821.2	24.88	6334	15.8	-9000	15500	26000	-46.0	75.0	130.0	-1300	1410	-700		
LX1892	A03948	0	819.3	25.03	7342	17.1	-4200	10000	20000	-25.0	82.0	124.0	-1260	950	-560		
LX1893	A03924	0	1081.7	27.82	9304	14.2	9200	21000	-24000	37.5	100.0	-110.0	-2150	1350	-1350	-0.17453	0.5236
LX1894	A03933	0	1063.3	27.74	9303	14.6	-11000	15000	24000	-53.0	62.0	120.0	-1950	-1300	-1350	0.26180	-0.5236
LX1895	A03951	1	1279.7	30.01	12698	12.9	-10000	16500	35000	-56.0	88.0	200.0	-1400	1900	-1650	-0.26180	-1.5708
LX1896	A03946	1	1287.4	30.19	14980	13.6	-6000	23000	12100	-31.5	80.0	62.0	-2400	-615	-1700	0.17453	0.0000
LX1898	A04101	0	318.6	15.03	1585	28.9	750	3800	-1600	5.3	41.5	-20.0	-660	90	-190		
LX1899	A04101	0	318.1	14.99	1413	27.9	1100	2750	-3200	14.3	26.5	-32.0	-560	255	-165		
LX1900	A04101	0	732.3	23.46	5690	16.8	3600	10000	-11000	22.0	66.0	-68.0	-1430	720	-590		
LX1901	A04101	0	731.5	23.56	5418	16.9	1800	10000	-6000	9.0	68.0	-28.0	-1640	370	-680		
LX1902	A04101	0	740.6	23.60	6232	17.1	1100	-5000	-2900	5.0	-30.0	-10.6	-1605	-440	-880		
LX1903	A04101	0	737.7	23.60	6308	17.2	2900	-5600	-4900	9.0	-27.0	-19.0	-1950	310	-940		
LX1905	A04101	1	1237.5	29.74	13814	13.6	7000	-8300	-11800	23.0	-35.0	-38.0	-2710	710	-1500	0.52360	0.0000
LX3006	AR0764	0	210.7	12.09	8748	36.5											
LX3007	AR0764	0	787.4	24.96	58023	17.8											
LX3008	AR0761	0	207.2	11.61	10473	37.9											
LX3009	AR0761	0	796.4	25.54	61617	18.1											
LX3010	AR0761	0	962.5	27.69	89665	16.7											
LX3011	AR0764	0	205.1	11.47	10231	38.6											
LX3012	AR0764	0	203.5	11.38	9650	37.5											
LX3013	AR0764	0	587.6	22.02	34768	22.7											
LX3014	AR0764	0	792.0	25.35	60237	17.9											

Data Set A

RUN	SUBJECT	FATALITY	PSA	ESV	ROO	DOP	QHA	QHB	QHC	RHA	RHB	RHC	AAX	AAY	AAZ	PHB	PFC
LX3015	AR0764	0	950.1	27.40	84844	16.4	.	.	.	.	.	.	.	.	.	-0.17453	1.5708
LX3016	AR0764	1	1216.6	30.77	138513	15.2	.	.	.	.	.	.	.	.	.	-0.17453	1.5708
LX3017	AR0761	0	209.1	11.74	10230	38.2	.	.	.	.	.	.	.	.	.	.	.
LX3018	AR0761	0	588.9	22.06	34373	22.7	.	.	.	.	.	.	.	.	.	.	.
LX3019	AR0761	0	416.5	18.51	19208	26.9	.	.	.	.	.	.	.	.	.	.	.
LX3020	AR0761	0	205.4	11.50	9128	37.1	.	.	.	.	.	.	.	.	.	.	.
LX3024	AR4107	0	98.0	6.67	950	54.4	-1060	1300	2020	-12.6	12.2	26.2	-176	-114	-45	.	.
LX3025	AR3923	0	95.6	6.58	599	51.9	-970	1190	2550	-13.0	18.4	38.0	-120	-165	42	.	.
LX3026	AR3923	1	1248.0	30.58	12922	13.2	-17000	15600	40000	-55.0	68.0	160.0	-3150	2900	-1300	-0.17453	-1.0472
LX3027	AR4114	0	101.4	6.55	4630	49.6	1210	2250	-3300	11.2	21.4	-35.5	-125	175	87	.	.
LX3028	AR4114	0	407.6	18.19	1804	24.0	3200	3400	-12500	37.0	15.0	-102.0	-810	-570	-365	.	.
LX3031	AR4115	1	1246.6	30.82	110585	12.8	.	.	.	.	.	.	.	.	.	0.26180	0.0000
LX3032	AR3936	0	1224.0	30.51	11540	13.1	16000	-14300	-10500	68.0	-70.0	-45.0	-2000	1120	-1320	1.04720	0.0000
LX3033	AR3936	1	1594.3	34.11	18719	11.8	40000	-7000	55000	.	.	.	.	.	.	1.04720	0.0000
LX3183	AR8824	0	103.1	6.90	558	48.9	-910	1100	700	-6.5	8.0	-7.2	-184	-52	-90	.	.
LX3184	AR8824	0	610.8	22.01	4111	21.5	10000	8200	-13000	44.0	50.0	-60.0	-1425	850	-550	.	.
LX3185	AR8857	0	100.2	6.93	641	52.2	.	1170	-720	-10.5	7.0	-22.0	-165	48	62	.	.
LX3186	AR8857	0	809.6	25.01	6287	15.7	12100	10800	-34000	62.0	60.0	-200.0	-1460	-1900	-1060	.	.
LX3187	AR8863	0	100.3	6.96	612	52.2	-975	1125	1150	-12.7	14.2	11.3	-170	-73	-63	.	.
LX3188	AR8863	0	1023.6	27.83	8180	13.7	-13500	16000	23500	-45.0	135.0	90.0	-2500	-1200	-850	-0.17453	-0.5236
LX3189	AR8866	0	101.0	7.02	1778	55.6	-1350	1150	2200	-15.0	9.0	28.0	-155	-108	-88	.	.
LX3191	AR8866	0	100.4	6.88	671	55.0	-670	1000	1000	-10.0	4.0	14.0	-216	-47	-108	.	.
LX3192	AR8866	1	1030.9	27.78	8769	13.6	12000	6000	-19000	49.0	17.0	-75.0	-2100	980	-775	0.52360	1.0472
LX3691	AR0012	0	99.2	6.71	1470	61.2	1010	320	-1650	19.5	8.4	-32.0	-130	92	-67	.	.
LX3692	AR0012	0	51.8	3.89	986	56.0	-560	325	920	-12.2	9.0	20.7	-61	-46	-26	.	.
LX3693	AR0012	0	726.3	23.32	4398	16.3	-9000	6200	14000	-50.0	45.0	78.0	-1400	-480	-700	.	.
LX3694	AR0012	0	766.7	23.59	5111	16.1	-16000	4900	27500	-75.0	31.0	135.0	-1140	-850	-800	.	.
LX3695	ARNA28	0	97.6	6.63	664	54.9	-700	1050	2300	-8.5	12.0	35.0	-100	-130	-60	.	.
LX3696	ARNA28	0	54.8	3.92	2138	53.0	240	650	-310	4.1	14.0	-5.3	-88	23	12	.	.
LX3697	ARNA28	0	440.3	18.91	2423	26.4	-7000	2750	15000	-44.0	31.0	100.0	-770	-610	-350	.	.
LX3698	ARNA28	0	435.5	18.86	1449	27.3	-7400	2750	16600	-45.0	32.0	103.0	-840	-650	-355	.	.
LX3699	AR8872	0	42.5	0.67	352	1.0	1600	900	-2500	22.5	17.0	-30.0	-140	128	-102	.	.
LX3700	AR8872	0	50.7	3.83	1453	59.6	370	520	-700	8.2	17.5	-13.0	-88	40	-30	.	.
LX3701	AR8872	0	436.0	18.85	2154	25.5	10000	5250	-14200	69.0	37.5	-108.0	-665	-620	-720	.	.
LX3702	AR8872	0	434.3	18.89	2201	26.3	12000	6000	-14000	70.0	48.0	-135.0	-700	-500	-680	.	.
LX3703	AR8802	0	99.2	6.80	661	53.3	-1600	1450	3000	-20.0	25.0	40.0	-110	-136	-13	.	.
LX3704	AR8802	0	51.7	3.90	1739	76.7	380	350	-450	13.3	10.7	-16.7	-28	50	27	.	.
LX3705	AR8802	0	629.5	22.32	3672	17.6	8100	14100	-16300	37.5	87.0	-82.0	-1165	690	-950	.	.
LX3706	AR8802	0	623.4	22.30	3786	18.7	10000	12500	-19000	42.0	73.0	-90.0	-1210	830	-910	.	.
LX3707	AR8790	0	98.2	6.64	726	47.0	520	805	-600	5.1	7.4	-7.0	-190	41	-105	.	.
LX3708	AR8790	0	50.6	3.90	1805	73.5	310	620	-750	7.7	13.0	-19.3	-55	48	33	.	.
LX3709	ARNA02	1	860.8	25.74	5660	15.3	16500	13500	-28000	60.0	51.0	-122.0	-1750	1200	-1040	-0.26180	1.0472
LX3710	ARNA02	0	97.4	7.78	641	55.6	700	-640	-700	9.0	-8.9	-10.2	-195	59	-117	.	.
LX3713	ARNA02	0	97.7	6.77	753	51.0	570	1550	-1260	6.8	21.0	-20.5	-195	73	-20	.	.
LX3714	ARNA02	0	598.6	21.88	3381	17.6	-2800	3700	8000	-16.0	17.0	50.0	-1460	290	-770	.	.
LX3715	ARNA02	0	598.9	21.92	3677	18.3	-3200	6700	11000	-21.5	36.5	80.0	-1220	350	-720	.	.

Data Set A

## APPENDIX B

The following two pages contain a listing of the sled experiments in Data Set B. Periods indicate missing values. A description of the variables is given in Table 1.

RUN	SUBJECT	FATALITY	INJURY	PSA	ESV	ROO	DOP	QHA	QHB	QHC	RHA	RHB	RHC	AAX	AAZ	PHA	PBB	PBC	
LX4781	AR6608	0	0	124.5	8.64	5147	48.0	400	1400	-1000	6	5	-18	-260	-85	-43	-0.27	0.41	0.60
LX4782	AR6608	0	0	124.2	8.63	5551	49.2	600	1800	-1100	3	-16	11	-280	-65	65	-0.20	0.86	0.22
LX4783	AR6608	0	0	556.0	21.49	45791	25.2	-2200	9100	-5100	-16	-55	25	.	-500	-350	-0.15	0.70	0.00
LX4784	AR6608	0	0	625.1	22.79	45328	23.4	-2500	12000	-5000	15	-45	35	-1800	-300	-680	-0.07	0.51	0.30
LX4785	AR6608	0	0	777.1	25.21	82057	22.6	12500	-8500	.	.	-46	.	-570	-300	-1100	-0.20	0.60	0.08
LX4786	AR6608	0	0	940.0	27.54	119035	20.4	2500	13000	-5800	-10	-58	17	-2400	-500	.	-0.15	0.67	0.00
LX4787	ARNR16	0	0	90.1	6.75	4457	56.1	320	1300	-510	5	-7	-5	-165	-23	-52	-0.20	0.54	0.38
LX4788	ARNR16	0	0	552.2	21.46	40681	24.1	2700	12000	-2200	10	-67	-12	-1200	-225	400	-0.30	0.85	0.30
LX4789	ARNR16	0	0	699.0	24.08	59345	23.4	4500	14000	-7500	30	-75	50	-1600	-270	470	-0.52	0.85	0.80
LX4790	ARNR16	0	0	834.4	26.08	18157	20.9	16000	11000	-24000	-55	60	95	-2100	950	-500	-0.25	-0.05	-0.45
LX4791	ARNR16	0	0	988.4	28.29	112651	19.3	12000	19000	-24000	-43	90	80	-2400	1050	-600	0.30	-0.20	-0.25
LX4792	ARNR21	0	0	95.5	7.12	4220	53.6	1000	650	-2400	16	10	-44	-140	60	28	0.55	-0.45	1.60
LX4795	ARNR21	0	0	985.1	28.39	123212	20.4	4500	19000	-10000	22	-105	-45	-2300	-550	700	-0.75	1.10	0.90
LX4798	ARNR18	0	0	104.3	7.42	4942	50.1	1500	750	2300	-22	16	40	-190	125	-60	0.17	-0.26	-1.10
LX4799	ARNR18	0	1	1039.6	29.04	133118	19.2	22000	16500	-30000	-82	75	130	-2800	1500	-510	0.30	-0.05	-0.80
LX4800	ARNR34	0	0	100.9	7.43	5721	53.3	-520	1820	-850	-6	24	10	-220	-34	30	0.11	-0.10	0.17
LX4801	ARNR34	1	4	994.7	28.38	133798	20.4	12000	50000	-7000	-40	250	20	-2600	1600	-2250	0.40	-1.00	0.00
LX4802	ARNR24	0	0	101.6	7.49	5859	54.0	1050	1100	-1700	18	19	-25	-220	-63	-35	-0.26	0.05	0.67
LX4803	ARNR24	1	4	884.1	26.40	98833	22.4	7000	19000	-14000	-26	71	35	-2500	260	-550	0.20	0.22	-0.10
LX4804	ARNR11	0	0	102.0	7.46	5539	52.6	1300	1300	-2400	13	15	-22	-270	-70	-57	0.14	-0.04	0.59
LX4806	ARNR11	0	0	838.5	26.17	103576	22.9	2400	1200	-4000	11	-68	-13	-2200	150	900	-0.20	1.20	0.15
LX4807	AR8739	0	0	101.1	7.39	5460	51.9	330	-800	200	5	-7	4	-200	-12	30	-0.34	0.68	0.11
LX4808	AR8739	0	0	544.4	21.38	45641	26.2	-3200	4300	6000	-24	-9	32	-1500	28	200	0.47	0.42	-0.45
LX4809	ARNR23	0	0	100.6	7.41	5337	52.6	-1300	1050	2700	-17	14	34	-220	-25	-27	0.22	0.02	-0.78
LX4810	ARNR23	0	0	545.2	21.37	42859	25.9	-10000	10000	16000	-61	54	100	-1300	700	240	0.02	0.02	-0.75
LX4811	AR8696	0	0	101.2	7.46	4826	53.0	680	950	-1500	-11	-7	20	-190	65	21	0.05	0.33	-0.53
LX4812	AR8696	0	1	845.4	26.29	105203	22.5	-7000	11500	-11500	-37	-38	35	-2500	550	-610	0.11	0.37	-0.40
LX4813	ARNR36	0	0	100.7	7.39	4891	53.2	-410	850	-1150	-5	10	-17	-210	40	-18	-0.65	0.47	0.01
LX4814	ARNR36	0	0	692.5	23.91	64523	23.9	-3400	11500	-7500	6	42	-38	-2100	-200	-450	-0.07	0.35	0.18
LX4815	ARNR40	0	0	101.0	7.34	4443	50.8	.	.	.	.	.	.	.	.	.	.	.	.
LX4816	ARNR40	0	0	700.3	24.02	68513	24.2	.	.	.	.	.	.	.	.	.	.	.	.
LX4817	AR8789	0	0	101.8	7.43	4289	51.7	-1100	750	2200	-18	-4	33	-175	78	-43	0.34	0.00	-1.06
LX4818	AR8789	0	0	700.0	24.05	66283	24.1	8000	-7200	12000	-36	-34	64	-2000	680	-450	0.30	0.55	-0.65
LX4819	AR8739	0	0	100.5	7.33	4140	48.6	-1000	1100	2200	-15	17	36	-160	-10	24	0.15	0.05	-0.95
LX4820	AR8739	0	0	545.0	21.32	42122	26.0	4400	10500	-7000	-17	48	34	-1500	290	-430	0.06	0.18	-0.21
LX4821	ARNR39	0	0	100.9	7.39	4337	50.0	-400	1400	-760	-4	18	7	-190	33	-32	0.11	0.23	-0.10
LX4822	ARNR39	0	0	842.6	26.23	89519	22.1	.	.	.	-7	22	-17	-2500	-190	-400	0.00	0.48	0.15
LX4823	AR6608	0	0	101.1	7.42	4625	53.3	250	1150	-350	3	-10	-5	-185	-22	-70	-0.15	0.44	0.10
LX4824	AR6608	0	0	1366.3	.	.	.	-3200	-11000	-3000	-20	-41	-10	-3500	-480	-920	0.00	0.50	-0.10
LX5122	AR0016	0	0	197.1	11.84	7443	36.7	-1250	-2500	1900	-15	-30	22	-370	-230	-70	-0.45	0.72	0.11
LX5123	AR0016	0	0	403.7	18.71	35669	34.2	2500	5000	-4100	13	-19	-25	-1200	1700	-370	0.20	0.21	0.30
LX5125	AR0016	0	0	720.0	24.53	60421	22.3	-1800	10500	3000	-10	-49	15	-1850	-80	-550	0.05	0.55	-0.08
LX5127	AR0016	0	0	200.1	12.09	9681	41.5	360	-2200	800	6	-26	7	-420	-82	-42	-0.41	0.75	0.11
LX5128	AR0016	0	0	406.4	18.70	20350	30.7	-3700	4600	-5000	12	-15	-31	-1000	-200	-280	0.18	0.33	0.32
LX5129	AR0016	0	0	724.5	24.58	66334	22.6	-2000	10500	2000	6	-48	-7	-1800	-230	-410	-0.17	0.62	0.14
LX5131	AR8858	0	0	724.5	24.58	66334	22.6	700	2500	-1200	9	-6	-14	-550	43	-220	0.04	0.10	0.20

Data Set B

RUN	SUBJECT	FATALITY	INJURY	PSA	ESV	ROO	DOP	QHA	QHB	QHC	RHA	RHB	RHC	AAX	AAZ	PHA	PHB	PFC	
LX5132	AR8858	0	0	408.2	18.78	19313	30.6	3500	4600	-6500	25	-16	-39	-1300	-185	-400	-0.03	0.28	0.40
LX5134	AR8845	0	0	201.6	12.21	8149	39.7	-850	3700	-1200	6	25	-10	-520	-60	-82	-0.12	0.24	0.13
LX5135	AR8845	0	0	409.2	18.84	21057	31.1	-1300	9500	1300	-3	55	5	-1100	-55	-215	-0.10	0.10	0.02
LX5137	ARNR16	0	0	200.5	12.13	7864	39.6	-1000	2000	-2000	-10	-13	17	-430	72	-92	0.04	0.50	-0.35
LX5138	ARNR16	0	0	413.9	18.99	20482	30.6	3500	3300	6600	-25	-13	44	-1000	240	-190	0.10	0.33	-0.48
LX5140	ARNR16	0	0	202.7	12.24	7471	39.1	-1200	2700	1820	-9	-16	15	-470	-85	-125	0.00	0.54	-0.22
LX5141	ARNR16	0	0	730.6	24.89	59887	22.3	-7000	13000	-2700	-16	-48	11	-1800	-130	-500	0.05	0.60	-0.15
LX5143	AR8858	0	0	203.4	12.27	7561	38.8	-1600	2300	2300	-13	23	20	-470	90	-180	0.12	0.18	-0.30
LX5144	AR8858	0	3	731.6	24.92	61773	22.6	1200	12500	1200	10	-33	8	-2100	65	-710	0.02	0.38	0.00
LX5146	AR8845	0	0	203.6	12.32	7587	39.3	-780	3600	-1600	5	28	-10	-460	-55	-85	-0.05	0.08	0.18
LX5147	AR8845	0	3	727.7	24.81	60409	22.5	10000	21000	9200	-26	120	50	-1380	400	-850	0.00	-0.40	-0.30
LX5149	ARNR16	0	0	202.9	12.24	7833	39.9	-520	3300	1700	-6	-20	16	-420	60	-140	-0.17	0.47	-0.30
LX5150	ARNR16	0	0	411.0	18.86	20914	31.0	-4600	4600	8800	-28	-5	52	-1050	330	-205	0.30	0.10	-0.52
LX5151	ARNR16	0	0	410.8	18.88	22789	31.9	-3500	3900	7100	-21	-11	44	-950	270	-240	-0.25	0.20	-0.50
LX5152	ARNR16	0	2	413.5	18.94	20193	30.6	-2900	4500	6200	-18	-12	38	-850	260	-240	-0.50	0.22	-0.45
LX5154	AR0016	0	0	204.6	12.29	7823	39.7	-520	-2200	800	-7	-26	6	-410	-65	-82	-0.17	0.64	-0.02
LX5155	AR0016	0	0	412.0	18.90	20099	30.5	-3000	2500	-3500	11	21	-35	-950	-180	-280	0.08	0.14	0.32
LX5156	AR0016	0	0	415.2	18.96	25639	31.8	-2800	3600	-3400	11	-6	-33	-910	-180	-320	0.15	0.12	0.38
LX5157	AR0016	0	0	411.1	18.79	20274	27.9	2600	3500	-4300	6	22	-25	-890	-135	-310	0.28	0.18	0.30
LX5159	AR0016	0	0	199.4	12.25	7027	40.1	-1000	-2400	2000	-10	-16	21	-400	-50	-100	-0.07	0.46	-0.25
LX5160	AR0016	0	0	723.9	24.60	74318	23.2	1700	10000	-1400	-8	-36	3	-1650	-145	-500	0.00	0.48	0.07
LX5161	AR0016	0	0	733.0	25.00	62816	22.8	3100	8800	2100	5	-35	8	-1650	-160	-520	-0.10	0.50	0.07
LX5162	AR0016	0	0	734.4	25.06	58484	22.3	-1800	11000	3500	5	-35	11	-1700	-170	-510	-0.18	0.50	0.06
LX5164	AR0016	0	0	732.5	24.81	56488	22.2	.	7600	.	-16	52	.	-1600	.	-500	0.00	-0.04	0.00
LX5165	AR0016	0	0	744.3	25.31	71209	22.8	4100	28000	2500	-38	155	.	-1500	200	-1200	0.00	-0.80	0.00

Data Set B



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REPORT DOCUMENTATION PAGE		READ INSTRUCTIONS BEFORE COMPLETING FORM
1. REPORT NUMBER 126-1	2. GOVT ACCESSION NO. <b>A173720</b>	3. RECIPIENT'S CATALOG NUMBER
4. TITLE (and Subtitle) FINAL REPORT ON STATISTICAL IMPACT ACCELERATION INJURY PREDICTION MODELS BASED ON -G <sub>x</sub> ACCELERATOR DATA		5. TYPE OF REPORT & PERIOD COVERED Technical Report
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19. KEY WORDS (Continue on reverse side if necessary and identify by block number) -G <sub>x</sub> Acceleration Logistic Response Model Impact Acceleration Injury		
20. ABSTRACT (Continue on reverse side if necessary and identify by block number) Since 1974, the Naval Biodynamics Laboratory (NBDL) has collected, as part of its research effort on acceleration impact injury prevention, an extensive data base from (-G <sub>x</sub> ) accelerator runs on Rhesus subjects. Over this time period, Desmatics, Inc. has been actively involved in the development of statistically based models to predict injury in Rhesus subjects resulting from indirect head/neck impact acceleration in the -X direction. The objectives of the present technical report are:  (continued)		

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- (1) to summarize, update, and consolidate the Desmatics modeling efforts for fatal injury;
- (2) to investigate extending the injury prediction models to include nonfatal injury criteria;
- and (3) to evaluate the accuracy and validity of the prediction models obtained in the modeling efforts.

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